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Determining China's CO_2 emissions peak with a dynamic nonlinear artificial neural network approach and scenario analysis

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ABSTRACT

The global community and the academic world have paid great attention to whether and when China's carbon dioxide (CO2) emissions will peak. Our study investigates the issue with the Nonlinear Auto Regressive model with exogenous inputs (NARX), a dynamic nonlinear artificial neural network that has not been applied previously to this question. The key advance over previous models is the inclusion of feedback mechanisms such as the influence of past CO2 emissions on current emissions. The results forecast that the peak of China's CO2 emissions will occur in 2029, 2031 or 2035 at the level of 10.08, 10.78 and 11.63 billion tonnes under low-growth, benchmark moderate-growth, and high-growth scenarios. Based on the methodology of the mean impact value (MIV), we differentiate and rank the importance of the influence factors on CO2 emissions whereas previous studies included but did not rank factors. We suggest that China should choose the moderate growth development road and achieve its peak target in 2031, focusing on reducing CO2 emissions as a percent of GDP, less carbon-intensive industrialization, and choosing technologies that reduce CO2 emissions from coal or increasing the use of less carbon-intensive fuels.

1. Introduction

China has become the world's largest CO2 emitter due to rapid industrialization and urbanization as well as relying on coal as the major energy source (Guan et al., 2008). China has explicitly proposed a goal of CO2 emissions peaking around 2030 in the "U.S.-China Joint Announcement on Climate Change" released in November 2014, and the Chinese government has reaffirmed this goal on many international occasions since then. It was a key component of "China's Intended Nationally Determined Contributions" submitted to the Secretariat of the United Nations Framework Convention on Climate Change in June 2015. It also guides China's energy transformation incorporated in the Energy Production and Consumption Transformation Strategy (2016–2030) released by the Chinese government in December 2016.

There are numerous studies predicting the year and level of peak emissions. One group of studies use regression analysis based on the IPAT identity, a linear relationship of how environmental impact depends on population, affluence (GDP per capita), and technology (resource intensity), although it can be augmented with additional variables. Another group of studies use Integrated Assessment Models (IAMs), complex interdisciplinary models that can incorporate nonlinear and dynamic relationships.

Both approaches have their limitations. Predicting a CO2 emissions peak is likely to require a nonlinear dynamic model to couple China's economy-energy-environment system and its evolution. IPAT-style models are linear and have a relatively simple theoretical underpinning. Some IAMs incorporate nonlinear and dynamic relationships. However, they have limits as long-term forecasting models. Kelly and Kolstad (1998) state that the primary purpose of IAMs is to educate, not to predict. Auffhammer and Carson (2008) object to the use of IAMs as forecasting models because they are not calibrated based on their out-of-sample predictive ability. Weyant (2017) characterizes IAM models as a good place to start, but a poor place to finish, in designing longer-term global policies. We apply the nonlinear autoregressive network with exogenous input (NARX) framework, a dynamic artificial neural network (ANN). Previous forecasting applications of the NARX model include electricity prices (Andalibab and Atrya, 2009), oil prices (Godarzi et al., 2014), and air pollution peaks (Pisoni et al., 2009,

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2011), but it has not been previously applied to CO2 emissions. In addition to capturing nonlinear and dynamic aspects of CO2 emissions, NARX and other ANN modes have self-learning capabilities, using both past input and output values to predict future CO2 output levels.

We incorporate scenario analysis and mean impact value (MIV) to predict the peak year, level, and influence factors of China's CO2 emissions. Of the three scenarios that we consider, our policy recommendation is a moderate growth scenario that will lead to a CO2 peak in 2031. A lower growth scenario leads to an earlier peak in 2029, but at too high a cost to China's well-being. Nor do we recommend a high-growth scenario that delays the peak to 2035, and results in a higher level of CO2 emissions.

Using mean impact value (MIV), we evaluate the influence of eleven influence factors on CO2 emissions. Based on their ranks, the three most important policies for China to meet its year 2030 goal are: continue the trends towards moderate growth in return for lower emissions, reduce manufacturing and construction in favor of services, and substitute lower emissions fuels for coal.

The paper proceeds as follows: Section 2 reviews existing studies on the economy-energy-environment system applicable to China, with particular attention to recent studies predicting the year and level of China's CO2 emissions peak that reflect China's pronouncements since 2014. Section 3 explains our methodology, the construction of the three scenarios (low-, medium-, and high-growth) for China, and data sources and NARX model processes. Section 4 presents results for the three scenarios. Section 5 provides conclusions and policy implications.

2. Literature relevant to estimating the peak of China's CO2 emissions

We review literature on China's CO2 emissions, focusing on studies that predict peak year and level based on CO2 policies China initiated in 2014. We then examine the literature findings, methods, the influence factors, the scenarios, limitations, and their relation to our study.

2.1. Research on China's CO2 emissions peak year and level

Many studies have systematically investigated the peaking year and level of China's CO2 emissions with scenario analysis, Environmental Kuznets Curve (EKC) analysis, optimal economic growth model analysis, decoupling analysis, and input-output analysis. China's CO2 emissions peaks vary by year and magnitude as revealed in existing studies.

Some empirical studies support a peak year in or after 2030 with various peaking levels, although most of these studies were done before China announced its concerted effort to reduce CO2 emissions in 2014 (e.g., United Nations Development Program (UNDP), 2009; Wang and Watson, 2010; Zhou et al., 2010; Du et al., 2015). Jiang et al. (2009) found different peaking levels with three scenarios: business as usual (BAU), low-carbon (LC), and enhanced low carbon (ELC). CO2 emissions from fossil fuel consumption peak from a high level of 12.93 billion tonnes in 2040 under the BAU scenario to a low level of 8.17 billion tonnes in 2030 under the ELC scenario. Liang and Guo (2010) found five different peaks with five scenario settings. Three of them occur after 2030, in 2043, 2035, and 2038. The study from Zhu et al. (2009) supports a peak in 2040. Although the study by Yue et al. (2010) supports a peak in 2035, the peak level of 16.13 billion tonnes is higher. The studies by Zhang et al. (2016) and Chai and Xu (2015) support a peak in 2030, with peak levels of 10 and 12 billion tonnes respectively.

Other studies support a CO2 emissions peak before 2030. Wang and Zheng (2013) found a peak of CO2 emissions around 2025 caused by decreasing energy consumption. Yuan et al. (2014) estimated a peak ranging from 9.2 to 9.4 billion tonnes and the time from 2025 to 2030. Lin and Li (2015), Mi et al. (2017), and Huang et al. (2017) also found a similar peaking year. Lin and Li (2016) found that China's CO2 emissions will peak at 13.18 billion tonnes in 2028 under the normal environmental regulation scenario, and the peak will advance to 2023 at 11.81 billion tonnes under stricter environmental regulations. Mi et al. (2017) found a peak of 11.2 billion tonnes in 2026 with an Integrated Model of Economy and Climate (IMEC) based on an input-output model and a scenario with an average growth rate of more than 5% in the future twenty years. China's CO2 emissions will peak in 2025 according to Huang et al. (2017), who use a mixed energy model based on energy demand and supply. The same peaking year is supported by the study from Chen (2017). Tang et al. (2018) investigated the electric power industry in six regions in China with a linear optimization model and found that China will achieve a CO2 peak by 2030, and in some regions by 2023.

Studies from scholars outside of China also support China's CO2 emissions peak occurring before 2030. den Elzen et al. (2016) applied a FAIR/TIMER IAM model in a bottom-up analysis framework and finds that China's CO2 emissions peak before 2030 with a set of "strengthened policies." Tollefson (2016) is confident about a peak before 2030. Green and Stern (2017) estimate a CO2 emissions peak on or before 2025 with a Kaya decomposition model based on IPAT and data from 2014 and 2015.

2.2. Prediction methodologies

Existing studies have applied numerous methodologies to predict CO2 emissions and its influencing factors. Two major types of methodologies are regression analyses based upon the IPAT identity and Integrated Assessment Models (IAMs). Table 1 summarizes recent representative studies, with reference to models, scenarios, and influences factors.

Integrated Assessment Models to investigate CO2 emissions include DICE/RICE (Nordhaus, 2017), MESSAGE (e.g., Messner and Schrattenholzer, 2000), C-GEM (e.g., Zhang et al., 2016), and FAIR/TIMER (e.g., den Elzen et al., 2016).[2] These models are based on either computable general equilibrium (CGE) or partial equilibrium models (e.g. FAIR/TIMER). IAMs connect economy, energy, emissions, and social factors. This complexity gives these models the advantages of quantifying changes and costs across the whole system. They are mainly used for estimating certain mitigation policy effects on the economy-energy-environment system based on scenarios, with rich policy implications for numerous economic sectors.

These energy models are further classified into two types based on the level of technological details: top-down models with the focus on aggregate variables and bottom-up models with the focus on technology-specific variables. Some studies (e.g., Gambhir et al., 2013; den Elzen et al., 2016) combine both top-down and bottom-up models in order to give policy recommendations based on the macroeconomic factors and the more detailed technological adjustments. However, there are drawbacks to their use as long-term forecasting models. As pointed out by some studies cited earlier, they are not calibrated based on their out-of-sample predictive ability. Furthermore, they are based upon neoclassical economic assumptions, including meeting policy goals at least cost. Predictions depend critically upon the assumptions, which vary for different IAMs. In addition, actual policies may reflect political feasibility rather than economic efficiency, so that neoclassical models that assume cost minimization may not predict accurately. Finally, they are biased towards "future as past," and cannot react to shocks nor to sudden changes in technology.[3]

[2] DICE/ RICE stand for Dynamic/Regionally Integrated Climate-Economy models, C-GEM is an acronym for China in Global Energy Market, FAIR is an acronym for Framework to Assess International Regimes and TIMER stands for The IMage Energy Regional Model. There are numerous other IAMs. Kriegler et al. (2015) compare eleven IAMs, including IMAGE, MESSAGE, and WITCH, among others.

[3] See Climate Brief (2018) for a discussion of the use and limitations of IAMs to study climate change.

Table 1
Recent representative studies of China's carbon dioxide emissions peak.

	Paper	Model	Scenarios	Influence Factors
1	Gambhir et al. (2013)	MESSAGE (IAM)	Baseline emissions, efficiency emissions, mix emissions (middle ground)	Population, GDP, urbanization
2	Yuan et al. (2014)	Kaya Identity (IPAT)	Different scenarios based on GDP growth and energy mixes	Population, GDP growth, industrial structure, urbanization, energy intensity, resident income, energy consumption, household energy consumption
3	Chai and Xu (2015)	IAM	Light Green, Deep Green, Light Blue, Deep Blue scenarios	Population, GDP growth, energy efficiency, urbanization
4	Zhang, Karplus, Qi, Zhang, and He (2016)	C-GEM (IAM)	No policy, continued effort, accelerated effort scenarios	Population, GDP, consumption growth, CO2 intensity
5	Wang, Zhu, Zhu, and Shi (2016)	Supply, demand, and technology hybrid energy model (IAM)	Simulation with one scenario of gradually rising oil prices	Energy structure changes, Oil price changes
6	den Elzen et al. (2016)	FAIR/TIMER, Bottom Up (IAM)	Current policies, Enhanced policies	Energy efficiency, forest management, hybrid vehicle subsidies and adoption, renewable energy
7	Mi et al. (2017)	Input-Output (Linear) (IAM)	Different scenarios for different variables listed in influence factors	GDP growth, energy consumption and fuel mix, industrial structure, and technological change (energy intensity)
8	Liu and Xiao (2018)	STIRPAT, System Dynamics model (IPAT)	Low, medium, and high scenarios for variables listed in influence factors	GDP, population, and energy consumption

The second group of studies employs regression analysis based on theories and models from ecological economics (e.g., IPAT, Kaya, STIRPAT) to investigate factors driving CO2 emissions (Azevedo et al., 2018; Ito, 2017) and predict future emissions (e.g., Auffhammer and Carson, 2008; Liu and Xiao, 2018).[4] The main purpose of this type of study is to understand the relationship between the major influence factors and CO2 emissions. The studies with the Kaya identity, a carbon-emissions-specific variant of IPAT, often include population, per capita GDP, energy consumption per unit of GDP, and energy carbon intensity (e.g., Yuan et al., 2014). Kaya and STIRPAT studies have included additional influence factors beyond the IPAT variables (see Table 1).

They often use reduced form models with advanced panel data or time series econometric techniques in order to reduce the influences from the confounding factors (e.g., unobserved heterogeneity, heteroskedasticity, and autocorrelation) and improve the estimation quality. The major drawback of this type of study is they usually use linear regression models, which are not able to capture the possible nonlinear relationships within the economy-energy-emission system.

In summary, the studies with large-scale energy models (e.g., IAMs) are able to quantify the impacts from certain policies on the entire economy-energy-emission system. This type of study is able to give rich policy recommendations with the breakdown of the economy-energy-emission system into aggregate or specific economic sectors, such as energy-intensive industries, electricity, and transportation. However, the primary motivation for this type of model is not long-term forecasting. The statistical studies with the IPAT model and its variants are limited by the linear functions and the aggregated influence factors of CO2 emissions (Lin et al., 1996; Mitrea et al., 2009; Godarzi et al., 2014).

3. Methodology

We predict China's CO2 emissions peak by integrating the NARX model, scenario analysis, and MIV.

3.1. The NARX model

This paper applies a NARX multi-variable model to predict China's CO2 emissions peak in the mid to long term. In addition to the features of ANNs, such as nonlinear mapping and self-learning, this model also has a memory property that not only connects output with the inputs and their lagged terms, but also with past outputs.

The equation for the NARX model is:

$$y(t) = f\left[y(t-1), y(t-2), \ldots, y(t-n), x(t-1), x(t-2), \ldots x(t-n)\right] \quad (1)$$

where $f[\bullet]$ is a nonlinear function, $y(t)$ is output, which is the targeted variable, $x(t)$ is network input, and $y(t-1), y(t-2), \ldots, y(t-n), x(t-1), x(t-2), \ldots, x(t-n)$ are time lags for the output and input variables. The structure of the NARX model for one input and one output is shown in Fig. 1. Both Eq. (1) and Fig. 1 can be generalized to show multiple inputs or outputs.

In Fig. 1, parameters d and m stand for the number of time delays and the number of neurons in the hidden layer (the layer between input and output layers) respectively. The prediction accuracy can be improved by adjusting these two parameters. W and b stand for the weight vectors. A set of weight vectors, w, correspond to a set of input vectors. They play a role similar to regression coefficients in relating inputs to

[4] The Kaya identity, developed by Yoichi Kaya, an engineer at Tokyo University, uses the IPAT identity to focus specifically on carbon emissions as the environmental impact. STIRPAT is an acronym for Stochastic Impacts by Regression on Population, Affluence and Technology, a generalization of IPAT that allows for regression, hypothesis testing, and the inclusion of additional variables beyond P, A, and T.

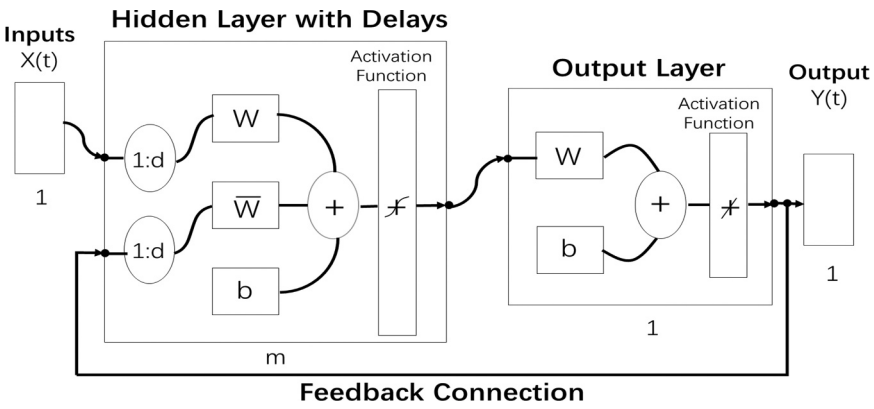

Fig. 1. NARX network structure (Peng and Lin, 2013)[a. a] In Fig. 1, the number of inputs and outputs is '1′, and the number of neurons in the hidden layer is 'm′. The figure shows a linear activation function between the hidden layer and the output layer, and a nonlinear (S-shaped) function between lagged output and current output, but we used nonlinear (S-shaped) functions for both activation functions.

the neurons, which are created variables in the hidden layer. W can be assigned any value before training, and it can be improved steadily by training. The term b is bias, analogous to the constant term in regression. This paper applies the Levenberg-Marquardt (LM) algorithm to adjust and update the weight vector w until the model converges to the targeted error.[5]

The weighted sum of all inputs determines the status (activated/non-activated) of a neuron, and it is shown as

$$net = \alpha \sum w_i x_i + \sum \bar{w}_i y_i + \beta \quad (2)$$

The status of activated or non-activated neurons is expressed with the threshold activation function:

$$\theta = \Psi(net) \quad (3)$$

This activation function is used to constrain the outputs of neurons within a certain proper range. The most popular threshold activation functions include a linear function, nonlinear gradient descent function, stepwise function, and S-shaped function. In NARX, the activation function for the hidden layer is an S-shaped (e.g. sigmoid) function, and the activation function for the output is a linear function.

The first step in a NARX model is to determine the inputs and outputs. The next step is to set up the number of nodes in the output and hidden layer. The number of nodes in the output layer is the number of output variables. The number of nodes in the hidden layer is determined based on the trial and error method and the size of errors. The data need to be classified into three sets, which are for training, validating, and testing. With recurrent training, the established model can be continuously improved to the point that it has a proper dynamic prediction ability to do scenario analysis for the peak of China's CO2 emissions.

The methodology to evaluate the model training and the accuracy of prediction includes root mean squared errors (RMSE), prediction accuracy R and error autocorrelation. RMSE measures the deviation of the predicted values from the observed values, and the prediction accuracy of the model is increased if the value of RMSE is lowered. Prediction accuracy R represents the degree of correlation between the prediction values and the observed values, and a high R value means the prediction is close to the observed value. Error autocorrelation represents the correlation between the errors from the prediction values and the observed values. An accurate prediction means that the difference between the two errors should be small enough to be statistically insignificant. This indicates that the values of error autocorrelation should mostly be within a certain confidence interval (e.g., 95%).

[5] The LM algorithm combines the gradient descent and the Gauss-Newton algorithm with a damping factor. Empirical studies shows that it is more efficient than the gradient descent. The drawback of the LM is that it may find only a local minimum instead of a global minimum. For more discussion and applications of the LM algorithm, see Kermani et al. (2005), Singh et al. (2007) and Mammadli (2017).

3.2. Influence factors of CO2 emissions and scenarios

3.2.1. Influence factors

Based on the studies reviewed in Section 2, we develop a system of factors affecting China's CO2 emissions, which includes industrialization, urbanization, gross economic output, economic structure, total population, energy consumption and structure, and energy productivity.[6] In addition, we also include the influence from environmental governance.

Industrialization, measured by GDP per capita (in yuan), captures the effects of industrial development on the level of CO2 emissions. Urbanization, measured by the proportion of urban population, explains the influences on CO2 emissions from the development of cities. Gross economic output, measured by GDP (in 100 million yuan), shows the effects of economic scale on the peak of CO2 emissions. The proportions of industry and service sectors–the secondary and tertiary sectors of China's economy (in %)–measure the effects of economic structure on the peak of CO2 emissions.[7] Total population (in 10 thousand) shows the influence of population on the CO2 emissions peak. Total energy consumption (in 10 thousand tonnes of coal equivalent (tce)) and the percentages of coal and non-fossil energy consumption measure the respective effects on CO2 emissions from energy consumption and its structure. GDP per unit of energy use (in 10 thousand yuan per tce) measures the effect on CO2 emissions from energy productivity.[8] Total investment in environmental governance (in 100 million yuan) measures China's efforts to manage CO2 emissions. All nominal variables such as GDP and GDP per capita are transformed to real values based on the 1978 CPI. All data are from the 2017 China Statistical Yearbook (CSY).

The influence factors add to the understanding of the peak mechanism of CO2 emissions in the following two aspects. First, we include eleven factors, a much larger number than has been considered in previous studies. From the perspective of influence direction, these factors can be divided into two categories: the positive factors that

[6] Although there may exist high multicollinearity among the factors, the NARX model can make full use of the learning ability, identify these related components, and reduce the impact of the correlation on the predicted value; this is one of the advantages of the model that is different from the traditional measurement model. As stated in Solares et al. (2017), "In the ideal scenario, the predictor variables will have a strong relationship to the dependent variable but should not be strongly related to each other." This problem is adequately solved by the NARX approach, since the NARX model can automatically eliminate redundant variables that cause multicollinearity.

[7] According to the national economy industry classification standard (GB/T 4754 – 2017), the primary industry is large agriculture, the secondary industry includes manufacturing and construction, and the tertiary sector is the service industry.

[8] Energy productivity equals the amount of GDP created by a unit of standard coal equivalent.

Table 2
Growth rates of influence factors of China's CO2 emissions (in %)[a].

Scenario	Time period	a1	a2	a3	a4	a5	a6	a7	a8	a9	a10	a11
Benchmark	2017–2030	6.5	6	0.5	T1:2.3 T2:1.3	T1: –3 T2: − 2	T1:3 T2:1.5	2	− 2.5	T1:9 T2:6	4	7
	2031–2040	5.5	5	T3:0.3 T4: − 0.4	0.5	− 1	0.5	1	− 2	3	3	7
	2041–2050	4.5	4	− 0.5	0.3	− 0.5	0.01	− 0.5	− 1	1	2	7
High-growth	2017–2030	7.5	7	0.5	T1:2.5 T2:1.5	T1: –3.5 T2: –2.5	T1:3.5 T2:2	2.5	− 2.5	T1:9 T2:6	4	7
	2031–2040	6.5	6	T3:0.3 T4: − 0.4	0.5	− 1.5	1	1.5	− 2	3	3	7
	2041–2050	5.5	5	− 0.5	0.3	− 1	0.5	− 0.5	− 1	1	2	7
Low-growth	2017–2030	5.5	5	0.5	T1:2 T2:1	T1: –2.5 T2: − 1.5	T1:2.5 T2:1	1.5	− 2.5	T1:9 T2:6	4	7
	2031–2040	4.5	4	T3:0.3 T4: − 0.4	0.5	− 0.5	0.5	0.5	− 2	3	3	7
	2041–2050	3.5	3	− 0.5	0.3	− 0.1	0.1	− 1	− 1	1	2	7

[a] Variables are: GDP (a1), GDP per capita (a2), total population (a3), urbanization rate (a4), percentage of secondary sector (a5), percentage of tertiary sector (a6), total energy consumption (a7), percentage of coal consumption (a8), percentage of non-fossil consumption (a9), energy productivity (a10), and total investment in environmental governance (a11). T1 is the time period from 2017 to 2020; T2 is 2021–2030; T3 is 2031–2035; T4 is 2036–2040.

increase CO2 emissions, including economic scale, industrialization, urbanization, total population, the proportion of the secondary industry, total energy consumption, and fossil energy consumption, and the reverse factors that decrease CO2 emissions, including the proportion of the tertiary industry, non-fossil energy, energy productivity and environmental governance.

Second, in the complex system of economy, energy and environment, the above factors interact and restrict each other within their respective influence scope, forming a peak trajectory in which CO2 emissions increase from a current level, reach a peak, and then decline from the peak. This path is the result of the internal coupling of these factors in the process of economic and social development. At the stage of accelerating industrialization and urbanization, the power of the subsystem composed of positive factors is greater than that of the subsystem composed of negative factors. This shows that the former's "marginal CO2 emissions" are larger than the latter's "marginal CO2 reduction." With technological advancement of industrialization and urbanization, the optimization and adjustment of industrial structure, the improvement of ecological governance and the improvement of energy efficiency, the marginal CO2 emissions of the former may be equal to the marginal CO2 reduction of the latter. At this point, peak CO2 emissions may occur. With the establishment of the main position of the tertiary industry and the completion of industrialization and urbanization, the marginal CO2 emissions of the former are less than the marginal CO2 reduction of the latter, and therefore reach a point at which the carbon dioxide emissions will decrease.

3.2.2. Scenarios

Based on the settings in existing studies (e.g. Jiang et al., 2009; Yuan et al., 2014; Energy Research Institute of NDRC, 2015; Wang and Zheng, 2013; CNPC Economics and Technology Research Institute, 2016, 2017; Liu and Wang, 2017), we present three scenarios in Table 2. We first explain the variable settings in the benchmark scenario. The high-growth and low-growth scenarios are then developed from the benchmark scenario with the adjustment of the influence factors corresponding to the characteristics of each stage in the Chinese mid-long term socioeconomic development process. All data used for scenario setting are from CSY (2017).

Under the benchmark scenario, according to the mean value of the past four decades (i.e. 1978–1987, 1988–1997, 1998–2007, and 2008–2116) and the settings in Energy Research Institute NDRC, China's Low Carbon Development Pathways by 2050 (2010), the GDP growth rate and GDP per capita growth rate are set at 6.5% and 6% respectively for 2017–2030. They decrease 1% in the next two decades (i.e., 2031–2040 and 2041–2050) based on historical experience of developed countries that GDP growth and the speed of industrialization will decline after a long period of rapid increase (Institute for Contemporary China Studies at Tsinghua University, 2017).

Based on the scenario settings by Jiang et al. (2009), population growth is set at 0.5% in 2017–2030 based on the mean value of the past four decades, 0.3% in 2031–2035, and declines to −0.4% and −0.5% respectively in 2036–2040 and 2041–2050 due to the increased cost and changing social norm of having children. Based on Li et al. (2017), we set the urbanization growth rate at 2.3% in 2017–2020, 1.3% in 2021–2030, 0.5% in 2031–2040, and 0.3% in 2041–2050.[9] The secondary and tertiary sectors are set up according to international experience and China's own development path; the secondary sector tends to decrease after the economy reaches a certain level of industrialization and urbanization, and the service sector tends to expand (Xu, 2010). So, according to the settings by Yuan et al. (2014), we set growth rates of the secondary sector as −3%, −2%, −1%, −0.5%, and the growth rates of the tertiary sector as 3%, 1.5%, 0.5%, and 0.01% respectively in 2017–2020, 2021–2030, 2031–2040, and 2041–2050.

Based on the total energy consumption and its structural change analysis by China's Energy Research Institute National Development and Reform Commission (NRDC) (2016) and energy consumption analysis by Shen et al. (2015), we assume that total energy consumption will also peak with slowed economic growth and improved energy efficiency, and set its growth rate at 2% in 2017–2030, 1% in 2031–2040, and −0.5% in 2041–2050. Coal consumption will keep decreasing according to national development strategy, and its rates of change are set for −2.5%, −2%, and −1% in each of the three periods. The growth rate for non-fossil energy will grow at a decreasing rate constrained by technology limits. Few studies have forecasted energy productivity development. We assume energy productivity also increases at a decreasing growth rate due to technology limits. The growth rates of total investment in environmental governance will grow at a constant rate because of the increasing attention paid by the state to CO2 emission control.

We then develop the high-growth and low-growth scenarios from the benchmark scenario. Under the high-growth scenario, the growth rates for GDP and GDP per capita continue at a higher level, and urbanization is initially higher (see Table 2). Industry structure transitions from manufacturing and construction to services at a faster rate. Total energy consumption increases at a higher rate due to a larger economic

[9] The urbanization rate is to be around 60% in 2020 and 70% in 2030 as planned in “National Population Development Plan (2016–2030)” prepared by the State Council of China.

scale even though there is a quicker transition from the secondary to the tertiary sector. We assume total population, coal and non-fossil energy consumption, energy productivity, and environmental protection have the same growth rates as they are in the benchmark scenario. In the low-growth scenario, as economic growth is slower than in the benchmark scenario, the growth rate of GDP, GDP per capita and urbanization are at a lower level. Overall, the power of economic scale is weaker than in the benchmark scenario, so there are lower total energy consumption changes even though there is a higher percentage of the secondary industry as compared to the benchmark scenario. We still assume the growth rates for total population, coal and non-fossil energy consumption, energy productivity, and environmental protection are the same as they are in the benchmark scenario.

3.3. Data

The data are from the China Statistical Yearbook (CSY) 2017 published by the National Bureau of Statistics in China, and the time period is 1978–2016. However, CO2 emission is not reported by CSY, so the quantity of CO2 emissions is estimated with a method developed by Xu and Song (2010). It is calculated by multiplying primary energies (coal, oil, natural gas, and non-fossil) by their respective carbon emissions coefficients, as shown in Eq. (4):

$$C = \sum_i \frac{E_i}{E} * \frac{C_i}{E_i} * E = \sum_i S_i * F_i * E * 44/12 \tag{4}$$

where C is CO2 emissions, E is total energy consumption, E_i is the consumption quantity of energy i, C_i is the quantity of carbon emissions from the i-th energy source; S_i denotes share of the i-th energy source in total energy consumption, F_i stands for carbon emission coefficients for each energy source, 44/12 is the ratio of carbon transformed into CO2.

The data are further normalized in order to better incorporate them into the NARX model. Data normalization enables an easier capture of the correlations between the independent variables and the dependent variables in a NARX model, which can improve the prediction accuracy of the model. This paper applies minimum-maximum normalization (see Eq. (5)), in which the data are normalized in the range from 0 to 1. The equation is:

$$Z_{norm} = \frac{Z - Z_{min}}{Z_{max} - Z_{min}} \tag{5}$$

where Z_{norm}, Z, Z_{max}, Z_{min} are normalized values, original values, and maximum and minimum in the original values.

3.4. Evaluation of influence factors

We apply a mean impact value (MIV) algorithm to quantitatively evaluate the influence factors of China's CO2 emissions. MIV is commonly used in ANNs to determine the relative importance of model inputs to the output.[10] The basic steps of MIV follow.

Assuming there are p inputs in the model, we get an independent variable vector space $X = [x_1, x_2, ..., x_m]$ through m times of observation on the independent variable vector composed of the p inputs. There is a dependent variable vector space corresponding to this X space, which is $= [y_1, y_2, ..., y_m]$. X is the vector of inputs of the NARX model, and its corresponding vector Y is the output. Train this model with the training data set, and then save the trained NARX. The next step is to add or subtract δ (in %) to/from the original values of the independent variables.[11] Two new independent variable vectors $X_i^{(1)}$ and $X_i^{(2)}$ are created through this step, and they are:

$$X_i^{(1)} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1m} \\ x_{21} & x_{22} & \cdots & x_{2m} \\ \vdots & \vdots & \cdots & \vdots \\ x_{i1}(1+\delta) & x_{i2}(1+\delta) & \cdots & x_{im}(1+\delta) \\ \vdots & \vdots & \cdots & \vdots \\ x_{p1} & x_{p2} & \cdots & x_{pm} \end{bmatrix}$$

$$X_i^{(2)} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1m} \\ x_{21} & x_{22} & \cdots & x_{2m} \\ \vdots & \vdots & \cdots & \vdots \\ x_{i1}(1-\delta) & x_{i2}(1-\delta) & \cdots & x_{im}(1-\delta) \\ \vdots & \vdots & \cdots & \vdots \\ x_{p1} & x_{p2} & \cdots & x_{pm} \end{bmatrix}$$

Taking these two newly created $X_i^{(1)}$and $X_i^{(2)}$as the inputs of the NARX model, we get the corresponding two output vectors $Y_i^{(1)}$and $Y_i^{(2)}$:

$$Y_i^{(1)} = [y_{i1}^{(1)}, y_{i2}^{(1)}, ..., y_{im}^{(1)}] \tag{6}$$

$$Y_i^{(2)} = [y_{i1}^{(2)}, y_{i2}^{(2)}, ..., y_{im}^{(2)}] \tag{7}$$

Then, the difference of subtracting Eq. (7) from Eq. (6) is $I_{vi} = Y_i^{(1)} - Y_i^{(2)}$, and this difference represents the vector of the change in the output value caused by the change of the i-th input variable for each sample point. This difference is then averaged by m. We then can get the mean impact value when the i-th input value changes, which is:

$$I_{MIV,i} = \sum_{j=1}^{m} \frac{I_{T,j}(j)}{m} \tag{8}$$

In Eq. (8), $I_{MIV,i}$ is the mean impact value on the output caused by the change of the i-th independent variable. Its sign represents the direction of the influence from the X to the Y, and its magnitude measures the comparative importance of the X to the Y. We can further get the contribution rate to the output from the i-th input, which is:

$$C_{MIV,i} = \frac{|I_{MIV,i}|}{\sum_{i=1}^{P} |I_{MIV,i}|} * 100\% \tag{9}$$

where p is the number of input variables.

4. Results and discussion

We set up the analysis based on the methodology introduced in Section 3: first, we set up socioeconomic development scenarios for China's CO2 emissions with the data from 1978 to 2016, and normalize the influence factors.[12] Next, we recurrently apply a trained NARX model to predict normalized CO2 emissions from 2017 to 2050, and then get the predicted amount of CO2 emissions by de-normalizing. We can therefore evaluate the year and level of China's CO2 emissions. The last step is to apply MIV to determine the magnitude and direction of the influence factors on the CO2 emissions. In an appendix, we compare our predictions to those obtained from a linear regression model and from a back-propagation model, a static ANN model where output depends only on current inputs.

4.1. Model evaluation

The NARX model development is the key step to predicting the peak of China's CO2 emissions. The output of the model is China's CO2 emissions, and the input is the influence factors of the CO2 emissions. Through testing, there are 10 neurons in the hidden layer and the time lag is 2. We use 70% of the data for training, and 15% of the data each for validating and testing.[13] The learning rate for training is 1000 time

[10] Zeng et al. (2017) use MIV to determine the relative importance of socioeconomic factors in forecasting electrical energy consumption in the U.S. and total energy consumption in China.

[11] δ is the proportion of change for each input variable.

[12] The software used in this paper is Matlab Neural Networks Toolbox (MathWorks Inc, 2016).

[13] Most NARX models use 70% for training and 30% for validation and testing. These parameters are self-determined by the model.

Table 3
RMSE and R of the NARX model.

	Target values	RMSE	R
training	27	0.0311	1.0000
validation	6	0.0011	0.9999
test	6	0.0429	0.9968

steps with the LM algorithm. Then quantitatively evaluate the trained model, and the results are shown in Table 3. From Table 3, we can see that this model's RMSE is less than 2.5% on average; R is close to 1; and the errors are all within the confidence intervals based on the training results. These results fit well with the requirements of the scenario analysis.

4.2. Peak summary

Inputting the normalized data (to 2050) of the influence factors into the trained NARX model, and then de-normalizing the prediction results, we get the peaks for China's CO2 emissions under the three scenarios. The predicted results are shown in Fig. 2. We find that the peak occurs in 2031, 2035, and 2029 under the benchmark, high-growth, and low-growth scenarios. The peak levels are 10.78, 11.63, and 10.08 billion tonnes respectively. We also find China's CO2 emissions per capita peaks in 2029 and 2028 at the level of 7.3 and 6.8 t under the benchmark and the low-growth scenarios, but CO2 emissions per capita will not peak under the high-growth scenario because even though CO2 emissions decrease after 2035, the rate of decrease is slower than the predicted decrease in population growth.

China's CO2 emissions peak at different rates of change under the three scenarios from 2017 to 2050. The results are shown in Fig. 3. First, China's CO2 emissions will either peak after the 15th Five-Year Plan (FYP) under the benchmark and the low-growth scenarios, or peak after the 16th FYP under the high-growth scenario. Second, the growth rates of China's CO2 emissions show opposite signs in the time periods before and after the peak. The growth rate is positive before the peak, and it is the highest under the high-growth scenario and lowest under the low-growth scenario. China's CO2 emissions decrease after the peak; the decrease rate is the largest under the benchmark, then the low-growth scenario, and the high-growth scenario has the smallest decrease. In addition, China's CO2 emissions decrease at an increasing rate under the low-growth scenario. During the 19th FYP, the rate exceeds the decreasing speed under the benchmark scenario. This renders distinctive differences in the level of CO2 emissions in 2050 under the three scenarios; specifically, CO2 emissions are 9.19 billion tonnes under the low-growth scenario, 9.29 billion tonnes under the benchmark, and 11.28 billion tonnes under the high-growth scenario.

Our estimates of CO2 peaking years and magnitudes in China are within the range of the predictions obtained in previous studies. According to the most optimistic scenarios of other studies, China is able to achieve a CO2 emissions peak as early as the early- to mid-2020s, such as the year 2023 (Liu and Xiao, 2018; Tang et al., 2018) and the year 2025 (Yuan et al., 2014; Lin and Li, 2015; Huang et al., 2017; Mi et al., 2017). The latest peaking years estimated in previous studies are around 2040 (e.g., Jiang et al., 2009; Liang and Guo, 2010). The CO2 emissions peaking level can reach as high as about 16 billion tonnes (e.g., Yue et al., 2010) and as low as about 8 billion tonnes (e.g., Jiang et al., 2009; Liu and Xiao, 2018).[14]

[14] The studies cited that find a peaking year of 2040 were done before China's commitment to peak by 2030. Similarly, the study cited that finds the high peaking level was done prior to the government's pledge to lower carbon emissions and reach a peak by 2030.

4.3. Influence factors

Based on the preceding analysis and according to the principle of MIV in the NARX model framework, we simulate the changes of China's CO2 emissions using data from 1978 to 2016. The simulation proceeds with adding and subtracting 1% for influence factors of China's CO2 emissions and then normalizing the data. The average influence values and contributions of the influence factors on CO2 emissions are calculated from Eqs. (8) and (9). Table 4 shows the results.

We investigate the influence factors of China's CO2 emissions comprehensively with the preceding analysis. Based on the results, we rank the importance of these factors from highest to lowest: economic scale (GDP), the proportion of the secondary sector, the proportion of coal consumption, industrialization, energy productivity, non-fossil energy consumption, total energy consumption, urbanization, total population, the proportion of the tertiary sector, and the investment in environmental governance.

We can compare our results broadly with the studies based on the IPAT models with linear regressions based on the importance of the influence factors. The study by Liu and Xiao (2018) reveal a rank with energy intensity as the highest impact, then GDP per capita, population, with energy structure having the least impact for China's CO2 emissions. Wang et al. (2017) show different levels of impacts from the influence factors at different stages of development in Xinjiang province of China. Economic growth is the dominant factor that increases CO2 emissions in Xinjiang during economic reform (1978–2012). Thus, economic growth is one of the most important factors in increasing CO2 emissions in China based on this brief comparison.

5. Conclusions and policy implications

With consideration of the non-linear development of the economy-energy-environment system, we investigated the peaks and influence factors of China's CO2 emissions by applying the NARX model under the dynamic machine learning framework, scenario analysis, and MIV. Our results estimated from the NARX model show that the peak is able to occur as early as 2029 under the low-growth scenario. The latest occurrence is in 2035 under the high-growth scenario. China's CO2 emissions will peak in 2031 under the benchmark scenario with moderate growth. Depending on the scenario, the peak level is between 10 and 11.7 billion tonnes. These results support China's commitment that CO2 emissions will peak around 2030.

The results of MIV reveal that the economic scale, secondary sector (manufacturing and construction), coal consumption, industrialization, and energy productivity contribute the most to CO2 emissions and its potential reduction. They provide a valuable reference to the developmental paths for China to achieve a CO2 emissions peak at a low level. The recent economic growth trend and the efforts that have been made to adjust economic structure and energy structure show that China is on its way to the CO2 emission peak estimated in this paper. Thus, China needs to stick with its economic development strategy and improve its policy implementation.

China's economic growth has entered a new normal since 2012, characterized by slower speed but higher quality of growth. The economic scale, the number one contributor to Chinese CO2 emissions, will likely expand at a moderate rate with lower economic growth rates in the future. The economic growth rates have been less than 7% for the past three years. The growth rate is likely to regress to the global mean after several decades of fast growth based on the international experience (e.g., Japan). Economic scale and CO2 emissions can be decoupled by adjusting economic structure. The main drivers of Chinese economic growth in the past were capital and energy-intensive manufacturing sectors, which caused a high MIV score for economic scale. With the change toward high quality economic growth, China has modified macroeconomic policies, including upgrading economic structure, significant investments in research and development, strengthening

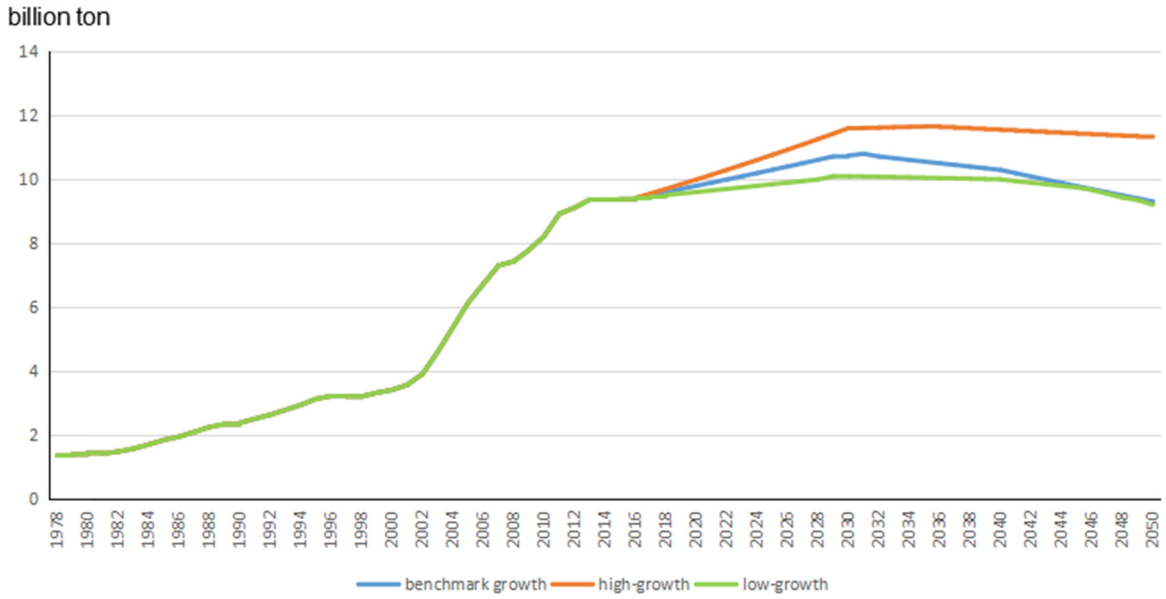

Fig. 2. China's CO2 emissions peaking path under different growth scenarios.

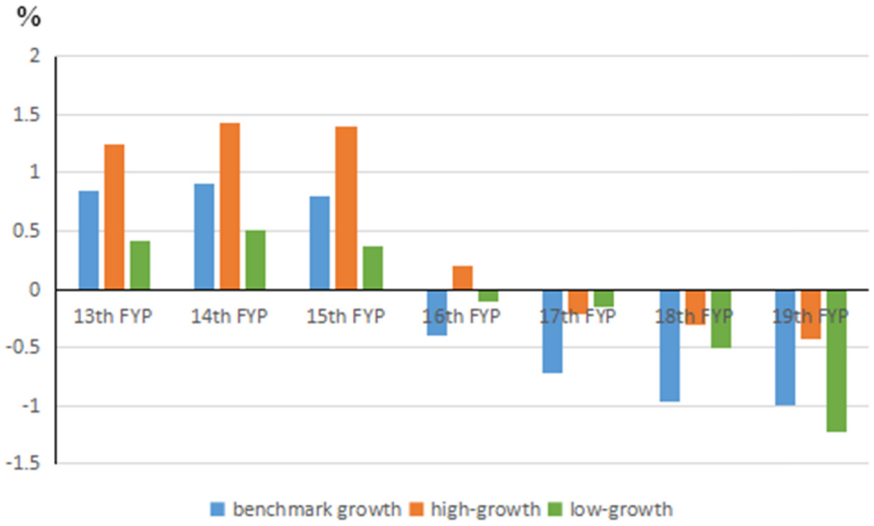

Fig. 3. Average growth rates for China's CO2 emissions under different scenarios[a]. [a]13th FYP: 2016–2020, 14th FYP: 2021–2025, 15th FYP: 2026–2030, 16th FYP: 2031–2035, 17th FYP: 2036–2040, 18th FYP: 2041–2045, 19th FYP: 2046–2050.

Table 4
MIV and contribution of the influence factors on China's CO2 emissions.

	MIV	Contribution (%)	Rank
GDP (0.1 billion yuan)	0.66527	12.23	1
Total population (10 thousand)	0.43217	7.95	9
Industrialization (yuan)	0.52059	9.57	4
Urbanization (%)	0.43282	7.96	8
Secondary sector (%)	0.60236	11.08	2
Tertiary sector (%)	0.39872	7.33	10
Total energy consumption (10 thousand TCE)	0.48739	8.96	7
Coal consumption (%)	0.55243	10.16	3
Non-fossil consumption (%)	− 0.48917	9.00	6
Energy productivity (10 thousand yuan per tce)	− 0.49672	9.13	5
Investment in environmental governance (0.1 billion yuan)	− 0.36035	6.63	11

intellectual property rights protection, reforming state-owned enterprises, curbing overcapacity, and advancing the role of the market in allocating resources across the economy. Of course, for these policies to be effective, the key is policy implementation.

The proportion of coal consumption is still increasing, but policies are aiming for a reduction. Nevertheless, from the efficiency perspective, this move away from coal as the major energy source should be balanced against other objectives since it is only one of the major contributors to CO2 emissions. For example, coal to gas heating conversion is controversial because in China, the cost of gas is still higher than coal and the supply of gas is not stable. In fact, coal to gas conversion caused heating shortages in some villages during the winter of 2018. As our paper shows, curbing CO2 emissions is a complex task and requires a policy regime that is able to coordinate contributing factors.

While dramatic reductions in China's economic growth and an accelerated transition from coal could bring about a carbon peak by 2029, the moderate growth path and a more gradual decrease in coal consumption delays the peak year to 2031, but achieves a higher level of overall economic well-being. Thus, we suggest that China should follow a moderate growth path and achieve its peak CO2 emissions in 2031 based on the results of this study and the current economic development stage in China.

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Appendix: Model comparison

In order to provide an indication of the advantages of the NARX model, we compare it with a linear regression model and a back-propagation (BP) neural network model. We do not compare the NARX model to an IAM model in this study because not all IAMs are publicly available, and there are a large number of such models, making a comparison difficult even if the models were available. Hence, we restrict the comparison to linear regression to show the advantage of a nonlinear model, and a BP neural network to show the advantage of including lagged exogenous input variables.

We first establish a linear regression model with the eleven influencing factors included in the NARX model as the explanatory variables of CO2 emissions, using the data from 1978 to 2016, and the database is from Section 3. The dependent variable is the quantity of CO2 emissions and the independent variables (i.e., the influencing factors) are transformed into natural logarithms. We develop this linear regression model with a stepwise regression method. We exclude influence factors with high multicollinearity (e.g., industrialization & energy productivity). Table A.1 shows the results from the final model.

Next, we use this linear regression model with the scenario settings as inputs to predict peaks of CO2 emissions. However, China's CO2 emissions do not peak with this model. CO2 emissions increase linearly with time under all three scenarios. The cause of this monotonic increasing trend is the dominant impact from GDP scale which is not counteracted by the increasing proportion of non-fossil energy and increasing environmental governance investments.

The other model used for comparison is a back-propagation (BP) model, a static neural network model. It is similar to the NARX model but with no consideration of past influences. It is composed of the same three layers as NARX: input, output, and hidden layers. There are eleven nodes/neurons (i.e., the eleven influence factors) in the hidden layer. CO2 emissions is the variable in the output layer. In this model, the training function is traindx[15] and we set up training error as 0.0001, training time as 10,000, and learning rate, which updates the weights, as 0.05.[16] We train this model with the normalized data from 1978 to 2010. We then test the model with the data from 2011 to 2016. We repeat this process until the model is optimized. Next, we use the normalized data from 2017 to 2050 in the scenario settings as inputs into the optimized BP model to predict normalized CO2 emissions. In the end we de-normalize the predicted CO2 emissions. The properties of the CO2 emissions peaks are shown in Table A.2. Compared to the NARX model, the peaking levels of CO2 emissions under the three scenarios are all higher with the BP model, and the peaks are delayed three to five years as compared to the peaks under the NARX model.

We use the Mean Absolute Error (MAE) and R-squared to compare the prediction quality from the linear regression, BP neural network, and NARX models (Table A.3). A lower MAE value indicates more accurate results. As shown in Table A.3, the results from the NARX model show both the lowest MAE and the highest R-squared, indicating that the prediction is more accurate than the other two models.

In sum, the predicted values of CO2 emissions based on the linear regression models are monotonically increasing which is not likely as most empirical studies do find peaks. The results from the BP model show the earliest occurrence of a peak is in 2034, which is four years later than the target set up by the Chinese government. Thus, the prediction results from the NARX model are more likely given the findings from existing studies and the policies of the Chinese government. The statistical properties of NARX are also the best among the three models.

Table A.1
Estimation results under the linear regression model.

Variable	Coefficient[a]	SE
ln(GDP)	7.130***	2.396
ln(total population)	0.127***	0.017
ln(urbanization rate)	0.091***	0.092
ln(percentage of secondary sector)	0.280***	0.102
ln(percentage of tertiary sector)	− 0.070***	0.004
ln(total energy consumption)	0.145***	0.008
ln(percentage of coal consumption)	0.200***	0.007
ln(percentage of non-fossil consumption)	− 7.320***	2.391
ln(total investment in environmental governance)	− 6.340***	2.431
constant	24.270**	11.002

[a] *** and ** represents coefficient is significant at the 0.01 and 0.05 level.

[15] Traindx is a network training function that updates weight and bias values according to gradient descent momentum and an adaptive learning rate. https://www.mathworks.com/help/deeplearning/ref/traingdx.html;jsessionid=c5e65cfe2f7ff83d31ece5787de6.

[16] In this model, the learning weight is chosen to be a small number so that weights are updated smoothly so as to avoid chaotic behavior.

Table A.2
China's carbon dioxide emissions peak under BP model.

Scenarios	Benchmark	High growth	Low growth
Peak level (billion tonnes)	11.21	13.13	10.95
Peak year	2036	2038	2034

Table A.3
Comparing accuracy of NARX to alternative models.

Model	Phase	MAE (%)	R^2
NARX	Training	2.98	1.0000
	Testing	3.51	0.9968
BP neural network	Training	5.83	0.9957
	Testing	8.16	0.9916
linear regression	N/A	6.15	0.9861

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